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A PRE-TRAINED FREQUENCY-PARAMETERIZED DEEP LEARNING IMPEDANCE TUBE METHOD TO ESTIMATE THE SOUND PROPAGATION CHARACTERISTICS IN POROUS MEDIA

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ABSTRACT

The normal incidence sound absorption properties of porous materials are most commonly measured using two-microphone impedance tubes. However, a single impedance tube measurement does not yield sufficient information to identify the material's sound propagation characteristics, *i.e.* the characteristic impedance and the wavenumber. More elaborate measurement techniques are required to obtain these, which demand more time, equipment, and enhanced user knowledge. This contribution presents a hybrid deep learning two-microphone impedance tube method, which estimates the sound propagation characteristics of a porous sample based on a single measurement conducted with a standard two-microphone impedance tube. A parameterized, fully convolutional encoder-decoder network processes the measured surface impedance and returns an estimate of the sample's characteristic impedance. The wavenumber follows from the measured surface impedance and the estimated characteristic impedance. The network is parameterized with respect to the measurement's frequency resolution. By doing so, the pre-trained network can process data stemming from arbitrary impedance tubes, accounting for any changes in microphone positioning or measurement sampling rates. We validate the proposed method with simulations of multiple specimens made of different porous materials. The proposed method significantly reduces the required resources and expenses for acoustic material characterization.

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1. INTRODUCTION

The standardized measurement method using a two-microphone impedance tube [1] is the most common technique for measuring the sound absorption coefficient of sound-absorbing samples. However, this measurement method can only determine the sound absorption coefficient given the normal incidence of a plane wave. In contrast to the plane wave sound field enforced in impedance tubes, spherical sound waves propagate in real, three-dimensional spaces and often impinge an absorbing panel at arbitrary angles of incidence. Under such real conditions, the absorption characteristics of the absorbing panel may differ significantly from those measured in the impedance tube, particularly when the absorbing panel is made from a material that exhibits non-local reaction behavior [2]. As a matter of fact, the absorbing panel may not perform as expected in its installed state, *i.e., in situ*. Measurements in a semi-anechoic chamber serve to determine the absorption behavior of such an absorbing panel under free-field conditions and hence, yield a reasonable estimate for its performance *in situ*. However, such an experimental procedure is laborious. Numerical simulations, *e.g.* by using the direct discrete complex image method [3], can be used to predict the sound absorption of a flat absorbing panel under free-field conditions. However, the sound propagation characteristics in the porous material, *i.e.,* the wavenumber and the characteristic impedance, need to be known for accurate sim-

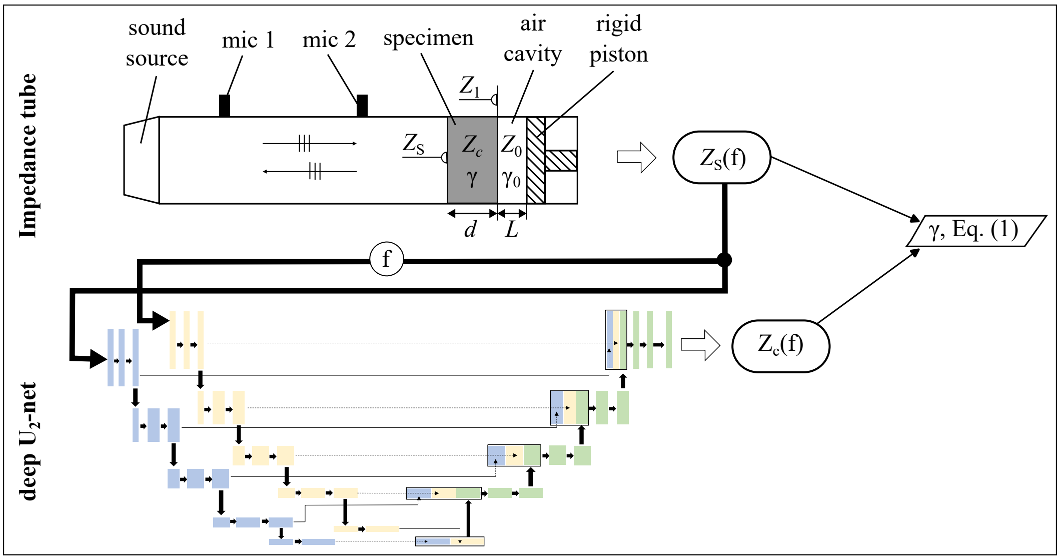

Figure 1. Process scheme of the frequency-parameterized hybrid deep learning impedance tube method.

ulation results. These sound propagation characteristics can be experimentally determined using the two-cavity method [4], the three-microphone impedance tube, or the four-microphone transmission tube method. However, these more elaborate methods require more time, equipment, and advanced user knowledge than the standardized two-microphone impedance tube method. In Ref. [5], the authors of this paper presented a hybrid method that combines a deep neural network with the two-microphone impedance tube method to reduce the measurement effort and resources required to determine sound propagation characteristics in porous media. In particular, a U-net is used for this purpose. While the traditional two-cavity method requires two individual measurements with a two-microphone impedance tube [4], the U-net replaces the second measurement in the hybrid method [5]. Consequently, the hybrid method adopts the analytic equations of the two-cavity method but uses only the outcome of one impedance tube measurement and the network's prediction to calculate the sound propagation characteristics.

This contribution aims at improving the hybrid deep learning impedance tube method introduced in Ref. [5] by introducing two adaptions: First, replacing the U-net architecture from Ref. [5] with a parameterized U-net architecture should enable the application of the hybrid method to arbitrary impedance tube setups. Second, the parameterized network is trained to estimate the characteristic impedance directly. This step aims to overcome one limitation of the hybrid method associated with using the analytic equations of the two-cavity method [5].

2. THEORY

The principle idea of the proposed method is to use a pre-trained deep neural network, which allows for flexible input dimensions, to estimate the sound propagation characteristics of a porous specimen based on a single measurement with a two-microphone impedance tube. Fig. 1 schematically shows the procedure for estimating the sound propagation characteristics using the pre-trained frequency-parameterized deep learning impedance tube method proposed in this work. At first, the normal incidence surface impedance Z_S of a compound made of the porous specimen under investigation (thickness d) and an air cavity of predefined thickness L is measured using the standardized two-microphone impedance tube method [1]. This measured surface impedance Z_S generally varies with the frequency f. Note that the measurable frequency range is limited by the geometry of the tube, in particular its inner diameter, and the distance between the microphones (mic 1 and mic 2) [1]. The frequency resolution of the measurement can be varied by adjusting the sample rate and the sample length in the data acquisition software. The measured surface impedance and the vector of discrete frequencies f serve as inputs to the deep neural network, which provides an estimate of the specimen's characteristic impedance $Z_c\,(f)$ with the identical frequency resolution as the measured surface impedance. The wavenumber in the porous specimen, γ, is then calculated from the measured surface impedance and the predicted characteristic impedance as [4]

$$\gamma\,(f) = \frac{1}{2\mathrm{i}d} \ln\left(\frac{Z_\mathrm{S} + Z_c}{Z_\mathrm{S} - Z_c}\frac{Z_1 - Z_c}{Z_1 + Z_c}\right), \tag{1}$$

where [4]

$$Z_1 = -\mathrm{i}Z_0 \cot\left(\gamma_0 L\right) \tag{2}$$

is the surface impedance at the interface between the porous specimen and the air cavity. It can be calculated from the free-field impedance of air $Z_0 = \rho_0 c_0$ and the wavenumber in air γ_0, where ρ_0 and c_0 are the mass density and the speed of sound in air. While the post-processing step to obtain the intrinsic wavenumber of the porous material, Eq. (1) is identical to that in the traditional two-cavity method [4] and in the originally proposed hybrid deep learning impedance tube method [5], the extensions proposed in this work enable a direct determination of the characteristic impedance based on a single two-microphone impedance tube measurement.

The centerpiece of the proposed method is a parameterized U_2-net, which has been inspired by the U_p-net proposed by Stender *et al.* [6]. This fully-convolutional encoder-decoder network uses multiple encoding paths, in this case, one for the measured surface impedance Z_S and a second one for the vector of discrete frequencies f, whose information is fused in one expansion path to provide predictions of one output quantity, the characteristic impedance, *cf.* Fig. 1. In contrast to the originally proposed hybrid deep learning impedance tube method [5], the additional encoder path, which deals with the vector of discrete frequencies, allows for a network parameterization concerning the measurement's frequency resolution. This enables the prediction of the characteristic impedance for arbitrary frequency ranges and resolutions, which is an essential asset in the light of integrating the hybrid deep learning impedance tube method into an impedance tube measurement software.

Training the parameterized network requires training data that include sufficient information on the dependency of Z_s and Z_c concerning the frequency. We rely on the data acquisition strategy outlined in Ref. [5] to generate numerical data to train the network. For the current study, the network is trained with input sequences of 800 frequency steps and surface impedance sequences corresponding to a specimen thickness of $d = 48$ mm and cavity thickness of $L = 20$ mm. Each numerical sample within the data sets comprises values of Z_S and Z_c for frequencies between 50 and 5000 Hz with a frequency resolution of 1 Hz. The network is trained with a batch size of 25 for 150 epochs, using 70 % of the data for training and 15 % for testing. The remaining 15 % of the data serve to validate the network's performance after the training has been completed. A scheduled learning rate is used, which reduces the learning rate after the first ten epochs and subsequently with every following epoch with a factor of $\exp(-0.1)$. Remark that re-training of the network is required if the specimen thickness d changes since the input surface impedance significantly depends on the specimen thickness.

3. RESULTS

Fig. 2 compares the U_2-net's predictions and the ground truth for the characteristic impedance of five selected samples of the validation data set. The real and imaginary parts of the predictions agree nearly perfectly with the numerical ground truth, which is additionally proven by the associated coefficients of determination (R_2 values). Note

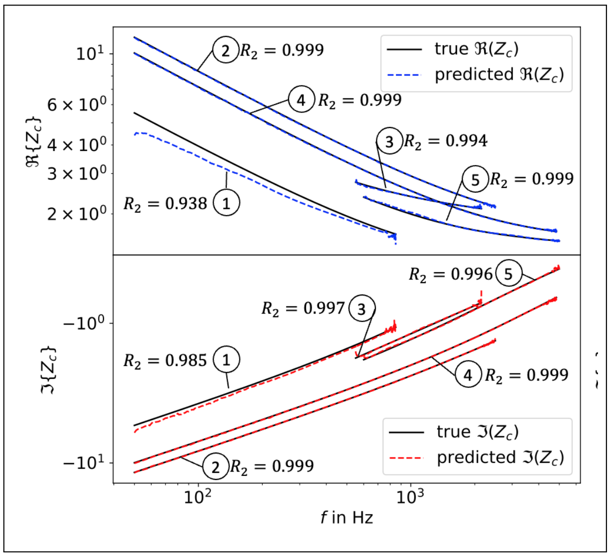

Figure 2. Comparison of the predictions of the characteristic impedance Z_c (real part: dashed blue, imaginary part: dashed red) and the ground truth (black solid) for five selected samples of the validation data set. R_2 values indicate the coefficient of determination.

that each of the five selected samples is defined on a different frequency range, proving that the proposed U_2-net architecture enables the hybrid deep learning impedance tube method to apply to various impedance tube measurement setups.

Fig. 3 shows the comparison between the enhanced hybrid method's estimates of the wavenumber and the ground truth for the selected samples 1 and 4 as indicated in Fig. 2. While the wavenumber for sample 1 is estimated with high accuracy, the estimate of the wavenumber for sample 4 shows high deviations for frequencies above 1000 Hz. This is because the argument of the complex-valued logarithm in Eq. (1) varies significantly, even though the characteristic impedance has been predicted nearly perfectly, *cf.* Fig. 2. This happens if the surface impedance Z_S, the characteristic impedance Z_c and the interface's impedance Z_1 have similar values for which the denominators in Eq. (1) potentially tend to zero. This effect has also been observed in the original hybrid deep learning impedance tube method [5], where Eq. (1) is also used to calculate the wavenumber. For a more detailed insight into this issue, the reader is referred to Ref. [5].

Further, the predictions of the characteristic impedance and the estimates of the wavenumber show deviations at the frequency ranges' beginning and end. These deviations are attributed to the zero padding applied in the up-convolution stages of the U_2-net, *cf.* Ref. [6].

In summary, the adaptions introduced in this work enable the hybrid deep learning impedance tube method to apply to any two-microphone impedance tube setup while yielding accurate, direct predictions of the characteristic impedance. However, in some cases, the wavenumber estimation suffers from the same issues as the original hybrid method.

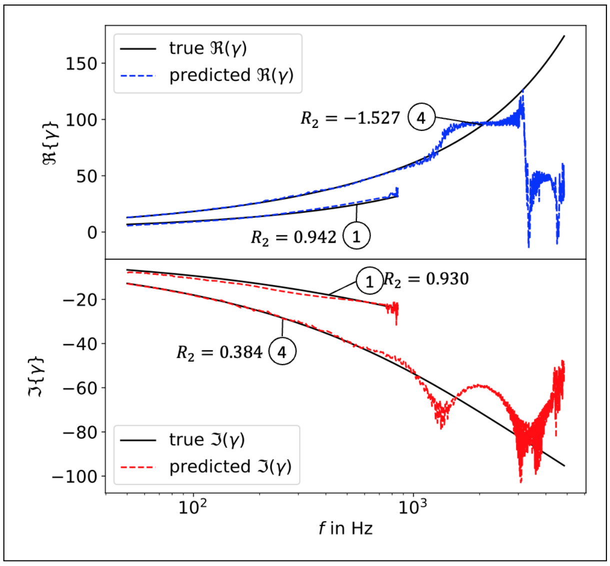

Figure 3. Comparison of the estimates of the wavenumber γ (real part: dashed blue, imaginary part: dashed red) and the ground truth (black solid) for the selected samples 1 and 4 as indicated in Fig. 2.

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